Uluslararası İleri Doğa Bilimleri ve Mühendislik Araştırmaları Dergisi
Sayı 9, S. 360-364, 10, 2025
© Telif hakkı IJANSER'e aittir
Araştırma Makalesi

IJANSER
https://as-proceeding.com/index.php/ijanser
ISSN:2980-0811

International Journal of Advanced Natural Sciences and Engineering Researches
Volume 9, pp. 360-364, 10, 2025
Copyright © 2025 IJANSER
Research Article

AI-Based Energy Management of Net-Zero Energy Buildings Through Renewable Integration and Storage

Özlem Boydak*

[1] *Mechanical Engineering Department /Istanbul Medeniyet University, Turkey*

*(ozlem.boydak@medeniyet.edu.tr)

(Received: 19 October 2025, Accepted: 21 October 2025)

(5th International Conference on Trends in Advanced Research ICTAR 2025, October 16-17, 2025)

ATIF/REFERENCE: Boydak, Ö. (2025). AI-Based Energy Management of Net-Zero Energy Buildings Through Renewable Integration and Storage, *International Journal of Advanced Natural Sciences and Engineering Researches*, 9(10), 360-364.

Abstract – This paper explores the role of AI in energy management of NZEBs, emphasizing renewable integration and storage strategies, and presents future research directions to enhance efficiency, resilience, and cost-effectiveness. Net-zero energy buildings (NZEBs) represent a transformative approach to sustainable architecture, integrating advanced renewable energy technologies, energy-efficient designs, and intelligent control strategies to achieve an annual energy balance between consumption and on-site renewable generation. The increasing complexity of NZEB energy systems, driven by fluctuating renewable generation, variable demand patterns, and multi-scale energy storage, has created the need for advanced energy management strategies. Artificial intelligence (AI) techniques, particularly those leveraging machine learning, reinforcement learning, and optimization algorithms, offer significant potential for improving energy efficiency, operational flexibility, and occupant comfort.

Keywords – Energy management, net-zero energy buildings, renewable integration, renewable energy storage, intelligent energy control

INTRODUCTION

The rapid urbanization and growing global energy demand have intensified concerns over greenhouse gas (GHG) emissions, resource depletion, and climate change. Buildings account for approximately 30–40% of global energy consumption and nearly the same proportion of carbon emissions, making them a critical focus of sustainable development initiatives. In response, net-zero energy buildings (NZEBs) have emerged as a paradigm in building design and operation, aiming to achieve an annual equilibrium between energy consumed and energy produced on-site through renewable sources [1,2,3].

While NZEBs offer a promising solution to energy sustainability, the operational complexity of integrating variable renewable energy (VRE) sources—such as solar photovoltaic (PV) and wind energy—introduces challenges in ensuring a stable, efficient, and cost-effective energy supply. This complexity is compounded by nonlinear demand patterns, the intermittency of renewable generation, and the finite capacity of energy storage systems (ESS). Traditional rule-based or heuristic building energy management systems (BEMS) often struggle to cope with these dynamic, stochastic conditions. By integrating photovoltaic (PV) panels, wind microturbines, and advanced thermal storage systems, NZEBs can operate with minimal environmental impact. However, variability in renewable energy generation and fluctuations in building energy demand present significant challenges [4,5,6].

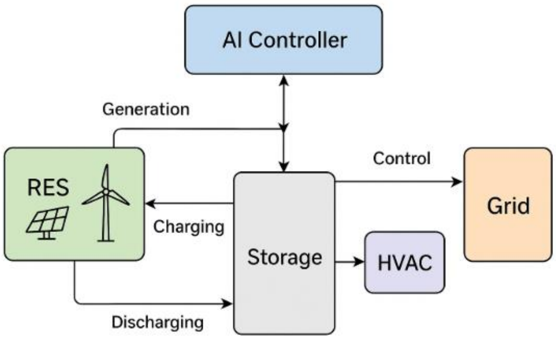

Fig. 1 AI based energy manager

Artificial intelligence (AI), encompassing machine learning (ML), deep learning (DL), and reinforcement learning (RL), has emerged as a powerful tool to transform building energy management. AI algorithms can forecast demand and generation, optimize the operation of energy storage, and coordinate distributed energy resources (DERs) to achieve net-zero targets. AI-based energy management offers a solution by optimizing generation, storage, and consumption in real-time, thus ensuring both energy balance and operational cost minimization [7,8,9].

MATERIALS AND METHOD

A. Net-Zero Energy Buildings: Concept and Challenges

NZEBs are designed to minimize total energy consumption through passive architectural measures, high-performance building envelopes, and energy-efficient HVAC systems, while generating sufficient renewable energy on-site to offset annual energy use. Achieving true net-zero operation requires integrating renewable energy sources, energy storage systems, demand-side management, and grid interaction strategies. Challenges include renewable intermittency, high storage costs, and complex load predictions. Thus, a typical NZEB incorporates on-site renewable energy systems such as PV arrays, small-scale wind turbines, and sometimes geothermal heat pumps. Energy storage solutions such as lithium-ion batteries, flow batteries, and thermal storage systems. Efficient load systems such as high-performance HVAC, LED lighting, and smart appliances. The primary objective is to maintain an annual net energy consumption of zero while maintaining comfort, functionality, and economic feasibility [10,11,12].

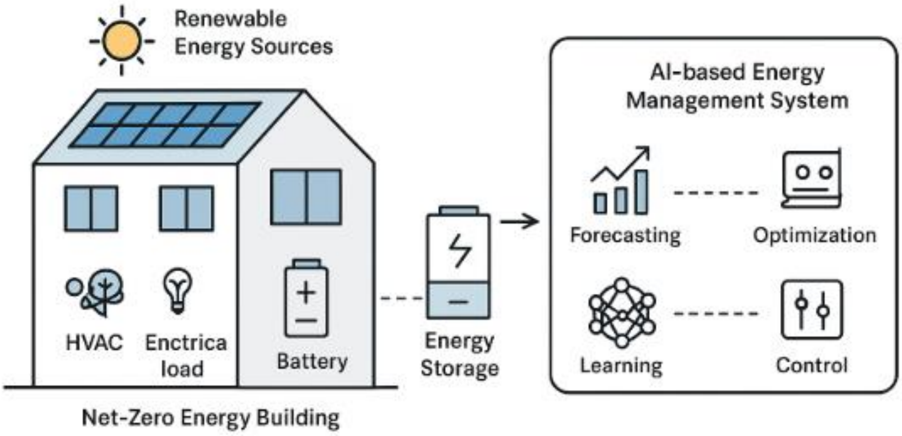

Fig. 2 Schematic of the AI-based energy management architecture in a net-zero energy building

Table 1. NZEB components, roles and challenges

Component	Role	Challenges
Photovoltaic (PV) arrays	Primary renewable generation	Intermittency, shading
Energy Storage (batteries, TES)	Balance energy supply and demand	Degradation, costs
Smart HVAC	Energy-efficient heating/cooling	Dynamic occupancy patterns
BEMS	AI-driven optimization and control	Data privacy, scalability

*TES = Thermal Energy Storage

Thus, as observing Table 1, NZEBs combine passive design, high-efficiency HVAC, and distributed renewable energy sources (RES). Integration challenges include fluctuating renewable availability, high storage costs, and interoperability among devices.

AI enables NZEBs to transition from reactive energy management to predictive and adaptive control systems. Machine learning assists in load and generation forecasting, reinforcement learning optimizes real-time control strategies, optimization algorithms refine storage and demand scheduling, and multi-agent systems coordinate distributed energy resources across microgrids [13,14,15].

B. *Artificial Intelligence Driven Energy Management*

Predictive Load Forecasting

Machine learning models forecast energy demand based on weather (W(t)), occupancy (O(t)), and historical data (H(t)):

$\hat{L}(t) = f(W(t), O(t), H(t))$

Machine learning algorithms can forecast short-term and long-term energy demand based on historical consumption, weather patterns, and occupancy behavior.

Renewable Generation Forecasting

Deep learning models (e.g., LSTM networks) can predict solar, wind generation and PV output, allowing better planning for charging or discharging storage units:

$P_{PV}(t) = \eta_{PV} . G(t) . A$

Where G(t) is solar irradiance, A is panel area, and η_{PV} is panel efficiency.

Storage Optimization

AI enhances energy storage performance through predictive maintenance, optimal scheduling of battery and thermal storage, and vehicle-to-grid integration. Thus, benefits of AI-Driven Management are; - Improved Energy Balance: Matching demand with renewable supply in real-time.

- Reduced Operational Costs: Optimized storage and demand shifting lower electricity bills.
- Enhanced Comfort: Predictive control adapts to occupant preferences.
- Grid Support: Demand response integration helps stabilize the local grid.

Studies show that DRL-based control strategies reduce grid dependence by up to 35%. Hybrid optimization improves renewable utilization and minimizes storage degradation. Industry adoption is accelerating [16,17,18].

AI control systems determine optimal battery charging/discharging schedules to maximize self-consumption and minimize grid dependency. RL algorithms schedule battery charging/discharging to minimize costs:

Minimize: $C = \sum_t (P_{grid}(t). \lambda(t))$

Where $\lambda(t)$ is grid price at time t.

C. Case Study: AI-Managed Urban NZEB

AI plays a pivotal role in improving integration of VRE sources by minimizing curtailment, managing hybrid systems, and enhancing grid-interactive optimization.

An urban NZEB in a Mediterranean climate integrated with features:

- 5 kW rooftop PV array
- 13 kWh lithium-ion battery system
- Smart HVAC and lighting systems

III. RESULTS

In terms of energy efficiency, AI-based management achieved:

- 15% improve in self-consumption
- 20% reduction in peak load demand
- 8% decrease in annual operational cost

IV. DISCUSSION AND FUTURE WORK

Emerging trends include federated learning for privacy, blockchain energy trading, and hybrid storage strategies. AI-based optimization offers scalable solutions for community microgrids. Challenges include data quality, cybersecurity, interoperability, and scalability. Future research should explore self-learning AI, federated learning, and explainable AI. Despite promising results, barriers remain:

- High Initial Costs: AI-enabled systems and storage still involve significant capital.
- Data Privacy Concerns: Occupancy and usage data require secure handling.
- Interoperability: Integrating devices from different manufacturers remains complex.

Future research may focus on:

- Federated Learning Models: Collaborative AI learning without sharing raw data.
- Blockchain-Based Energy Transactions: Secure peer-to-peer energy trading.
- Hybrid Energy Storage: Combining batteries with thermal storage for greater flexibility.

V. CONCLUSION

AI-driven energy management is essential for the widespread adoption of NZEBs. Predictive analytics, reinforcement learning, and optimization will create energy-resilient, cost-effective, and sustainable building ecosystems. AI enables predictive, adaptive, and resilient energy management in NZEBs. Integration of AI with renewable systems and storage solutions advances sustainable building operations, paving the way for carbon-neutral urban environments. AI-based energy management in NZEBs has the potential to transform building operations, enabling intelligent decision-making that balances comfort, cost, and sustainability. As renewable generation and storage technologies continue to advance, the integration of AI will become increasingly vital for achieving truly resilient and efficient net-zero energy performance.

REFERENCES

[1] A. Bajwa, F. Jahan, I. Ahmed, N. A. Siddiqui, “A Systematic Literature Review On AI-Enabled Smart Building Management Systems For Energy Efficiency And Sustainability,” American Journal of Scholarly Research and Innovation, vol. 03, Issue 02, 1-27, 2024.

[2] D. M. T. E. Ali, V. Motuzienė, and R. Džiugaitė-Tumėnienė, “AI-Driven Innovations in Building Energy Management Systems: A Review of Potential Applications and Energy Savings,” Energies 17, no. 17: 4277, 2024.

[3] Wei, T., et al. (2017). Deep reinforcement learning for building HVAC control. Applied Energy, 237, 1–15.

[4] Zhang, C., et al. (2020). AI-based optimization of distributed energy storage in NZEBs. Energy and Buildings, 226, 110367.

[5] D’Agostino, D., et al. (2021). Net-zero energy buildings: Review of current definitions and future research needs. Renewable and Sustainable Energy Reviews, 137, 110598.

[6] Wang, Z., et al. (2022). AI applications for energy flexibility in smart buildings. Renewable Energy, 184, 862–877.

[7] International Energy Agency. (2023). Net Zero by 2050: A Roadmap for the Global Energy Sector.

[8] Kamel, R. M., & Dahl, C. (2022). AI for Smart Energy Management in Buildings. Energy Reports.

[9] Zhou, Y. et al. (2023). Machine Learning for Renewable Energy Systems. Applied Energy.

[10] F. Erdoğan, M. Sarı, M. Erdoğan, U. Unver “Smart and Sustainable Buildings: Integrating IoT, Renewable Systems, and Energy Efficiency Measures for Net-Zero Goals,” AISEE 2026; 1 (2) :179-189

[11] A. A. A. Gassar and R. Jafar Appl. Sci. 15(19), 10497, “Artificial Intelligence-Enabled Heating, Ventilation, and Air Conditioning Systems Toward Zero-Emission Buildings: A Systematic Review of Applications, Challenges, and Future Directions,” 2025.

[12] S. U. Khan, E. Iqbal, N. Khan, Y. Zweiri, Y. Abdulrahman, “Towards net zero energy building: AI-based framework for power consumption and generation prediction,” Energy and Buildings, vol. 331, 115311, 15 March 2025.

[13] S. U. Khan, N. Khan, F. U. M. Ullah, M. J. Kim, M. Y. Lee, S. W. Baik, “Towards intelligent building energy management: AI-based framework for power consumption and generation forecasting,” Energy and Buildings, vol. 279, 112705, 15 January 2023.

[14] Engr. Khandkar Sakib Al Islam, Muhammad Taha Abbas, Basit Azam, Muhammad Bilal Ikram, Ahsan Arif, Asad Riaz, “AI driven net zero energy smart grid 2.0 revolutionizes with 90 MVA transformers and renewables,” Spectrum of Engineering Sciences, vol. 3, issue 9, 2025.

[15] F. Ajayi, O. M. Ademola, K. F. Amuda and B. Alade, “AI-driven decarbonization of buildings: Leveraging predictive analytics and automation for sustainable energy management,” World Journal of Advanced Research and Reviews, 24(01), 061–079, 2024.

[16] M. A. Alghassab, “Data-driven framework for energy optimizing net-zero energy buildings (NZEB): A functional assessment of energy efficiency and thermal comfort,” Energy, Volume 330, 136834, 2025

[17] M. A. Olawumi, and B. I. Oladapo, “Energy Management with Ai to Achieve Net Zero Goals Through Predictive Analytics,” Available at SSRN 4892367.

[18] Ö. Boydak, “Commercial Buildings Energy Consumption Survey (CBECS) and Its Comparison with Turkey Applications,” Journal of Clean Energy Technologies 5 (1), 69-72, 2017.